Creating Cohorts of Songs

Problem Scenario:

The customer always looks forward to specialized treatment, whether shopping on an e-commerce website or watching Netflix. The customer desires content that aligns with their preferences. To maintain customer engagement, companies must consistently provide the most relevant information. Starting with Spotify, a Swedish audio streaming and media

service provider, boasts over 456 million active monthly users, including more than 195 million paid subscribers as of September 2022. The company aims to create cohorts of different songs to enhance song recommendations. These cohorts will be based on various relevant features, ensuring that each group contains similar types of songs.

Problem Objective:

As a data scientist, you should perform exploratory data analysis and cluster analysis to create cohorts of songs. The goal is to better understand the various factors that create a cohort of songs.

In [111…

```
#importing required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
os.environ["OMP_NUM_THREADS"] = "7"

def make_pretty(styler):
    styler.set_caption("Top 2 Albums")
    styler.background_gradient(axis=None, vmin=1, vmax=5, cmap="YlGnBu")
    return styler
```

Steps to Perform:

1. Initial data inspection and data cleaning: a. Examine the data initially to identify duplicates, missing values, irrelevant entries, or outliers. Check for any instances of erroneous entries and rectify them as needed.

2. Refine the data for further processing based on your findings

In [111…

```
#Reading and Inspecting data
df = pd.read_csv('rolling_stones_spotify.csv')

# Inspecting the first few rows of the DataFrame
print(df.head())
```

```
# Displaying the last few rows of the DataFrame
#print(df.tail())

# Providing information about the DataFrame, including data types and non-null coun
print(df.info())
```

```
   Unnamed: 0                         name             album release_date  \
0           0   Concert Intro Music - Live  Licked Live In NYC   2022-06-10
1           1   Street Fighting Man - Live  Licked Live In NYC   2022-06-10
2           2           Start Me Up - Live  Licked Live In NYC   2022-06-10
3           3  If You Can't Rock Me - Live  Licked Live In NYC   2022-06-10
4           4            Don’t Stop - Live  Licked Live In NYC   2022-06-10

   track_number                      id                                   uri  \
0             1  2IEkywLJ4ykbhi1yRQvmsT  spotify:track:2IEkywLJ4ykbhi1yRQvmsT
1             2  6GVgVJBKkGJoRfarYRvGTU  spotify:track:6GVgVJBKkGJoRfarYRvGTU
2             3  1Lu761pZ0dBTGpzxaQoZNW  spotify:track:1Lu761pZ0dBTGpzxaQoZNW
3             4  1agTQzOTUnGNggyckEqiDH  spotify:track:1agTQzOTUnGNggyckEqiDH
4             5  7piGJR8YndQBQWVXv6KtQw  spotify:track:7piGJR8YndQBQWVXv6KtQw

   acousticness  danceability  energy  instrumentalness  liveness  loudness  \
0        0.0824         0.463   0.993          0.996000     0.932   -12.913
1        0.4370         0.326   0.965          0.233000     0.961    -4.803
2        0.4160         0.386   0.969          0.400000     0.956    -4.936
3        0.5670         0.369   0.985          0.000107     0.895    -5.535
4        0.4000         0.303   0.969          0.055900     0.966    -5.098

   speechiness    tempo  valence  popularity  duration_ms
0       0.1100  118.001   0.0302          33        48640
1       0.0759  131.455   0.3180          34       253173
2       0.1150  130.066   0.3130          34       263160
3       0.1930  132.994   0.1470          32       305880
4       0.0930  130.533   0.2060          32       305106
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1610 entries, 0 to 1609
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Unnamed: 0        1610 non-null   int64
 1   name              1610 non-null   object
 2   album             1610 non-null   object
 3   release_date      1610 non-null   object
 4   track_number      1610 non-null   int64
 5   id                1610 non-null   object
 6   uri               1610 non-null   object
 7   acousticness      1610 non-null   float64
 8   danceability      1610 non-null   float64
 9   energy            1610 non-null   float64
 10  instrumentalness  1610 non-null   float64
 11  liveness          1610 non-null   float64
 12  loudness          1610 non-null   float64
 13  speechiness       1610 non-null   float64
 14  tempo             1610 non-null   float64
 15  valence           1610 non-null   float64
 16  popularity        1610 non-null   int64
 17  duration_ms       1610 non-null   int64
dtypes: float64(9), int64(4), object(5)
memory usage: 226.5+ KB
None
```

In [111…

```
# Checking for missing values
missing_values = df.isnull().sum()
```

```
print("Missing Values per Column:")
print(missing_values)
```

```
Missing Values per Column:
Unnamed: 0          0
name                0
album               0
release_date        0
track_number        0
id                  0
uri                 0
acousticness        0
danceability        0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
duration_ms         0
dtype: int64
```

In [112…

```
# Find duplicate rows
duplicates = df[df.duplicated()]
print(duplicates)

# Removing duplicate records
df_no_duplicates = df.drop_duplicates()
```

```
Empty DataFrame
Columns: [Unnamed: 0, name, album, release_date, track_number, id, uri, acousticnes
s, danceability, energy, instrumentalness, liveness, loudness, speechiness, tempo, v
alence, popularity, duration_ms]
Index: []
```

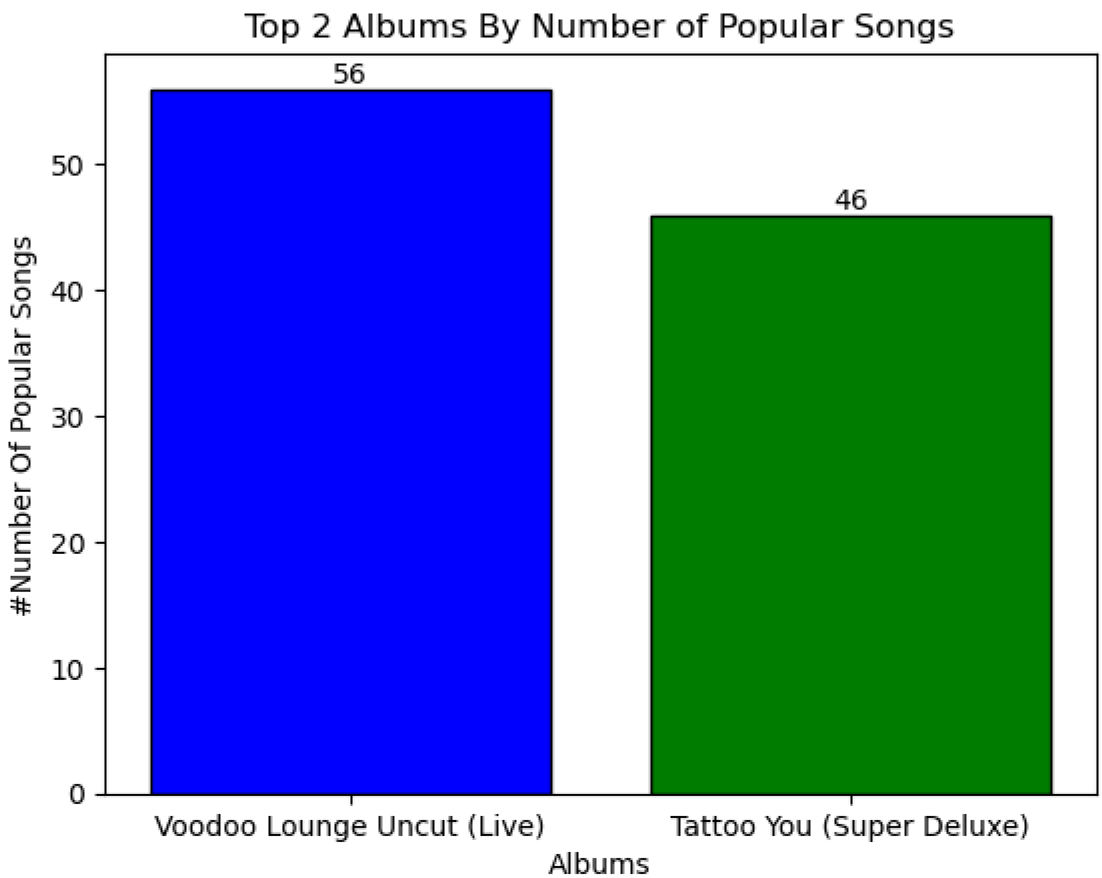
a. Utilize suitable visualizations to identify the two albums that should be recommended to anyone based on the number of popular songs in each album.

In [112…

```
# Filtering Album based on popularilty score, keeping where score greater than 0
dfpopular= df[df['popularity'] > 0].copy()

result = dfpopular.groupby(['album']).agg(
    NoOfPopularSongs=('popularity', 'count'),
    SumOfPopularity=('popularity', 'sum'),
   )

Top5Album_df=result.sort_values(['NoOfPopularSongs'],ascending=False).head(2).reset
print("Tracks are filter out based on criteria where popularity score>0")
#print(Top5Album_df)

# Create a bar chart
colors = ['blue', 'green', 'orange']
b=plt.bar(Top5Album_df['album'],Top5Album_df['NoOfPopularSongs'],edgecolor='black',
```

```python
# Add Labels
plt.xlabel('Albums')
plt.ylabel('#Number Of Popular Songs')
plt.bar_label(b)
plt.title('Top 2 Albums By Number of Popular Songs')

# Show the plot
plt.show()

Top5Album_df.style.pipe(make_pretty)
```

```
Tracks are filter out based on criteria where popularity score>0
```



Out[112…

Top 2 Albums

	album	NoOfPopularSongs	SumOfPopularity
0	Voodoo Lounge Uncut (Live)	56	654
1	Tattoo You (Super Deluxe)	46	1008

b. Conduct exploratory data analysis to delve into various features of songs, aiming to identify patterns

In [112…

```python
# Displaying descriptive statistics of the DataFrame, such as mean, std, min, max,
print(df.describe())
```

```
       Unnamed: 0  track_number  acousticness  danceability       energy  \
count  1610.000000   1610.000000   1610.000000   1610.000000  1610.000000
mean    804.500000      8.613665      0.250475      0.468860     0.792352
std     464.911282      6.560220      0.227397      0.141775     0.179886
min       0.000000      1.000000      0.000009      0.104000     0.141000
25%     402.250000      4.000000      0.058350      0.362250     0.674000
50%     804.500000      7.000000      0.183000      0.458000     0.848500
75%    1206.750000     11.000000      0.403750      0.578000     0.945000
max    1609.000000     47.000000      0.994000      0.887000     0.999000

      instrumentalness    liveness     loudness  speechiness        tempo  \
count      1610.000000  1610.00000  1610.000000  1610.000000  1610.000000
mean          0.164170     0.49173    -6.971615     0.069512   126.082033
std           0.276249     0.34910     2.994003     0.051631    29.233483
min           0.000000     0.02190   -24.408000     0.023200    46.525000
25%           0.000219     0.15300    -8.982500     0.036500   107.390750
50%           0.013750     0.37950    -6.523000     0.051200   124.404500
75%           0.179000     0.89375    -4.608750     0.086600   142.355750
max           0.996000     0.99800    -1.014000     0.624000   216.304000

          valence   popularity    duration_ms
count  1610.000000  1610.000000    1610.000000
mean      0.582165    20.788199  257736.488199
std       0.231253    12.426859  108333.474920
min       0.000000     0.000000   21000.000000
25%       0.404250    13.000000  190613.000000
50%       0.583000    20.000000  243093.000000
75%       0.778000    27.000000  295319.750000
max       0.974000    80.000000  981866.000000
```

c. Examine the relationship between a song's popularity and various factors, exploring how this correlation has evolved

In [112…

```
#Examine the relationship between a song's popularity and various factors, explorin
dfcor=df[['acousticness','energy','liveness','loudness','speechiness','tempo','vale
#dfcor=dfcor[dfcor['speechiness']<=0.33]
print('Corelation between features')
dfcor.corr()
```

```
Corelation between features
```

Out[112…

	acousticness	energy	liveness	loudness	speechiness	tempo	va
acousticness	1.000000	-0.363819	-0.117739	-0.237083	-0.021774	-0.171003	-0.1
energy	-0.363819	1.000000	0.511188	0.698039	0.417214	0.201885	0.0
liveness	-0.117739	0.511188	1.000000	0.327036	0.400018	0.108855	-0.3
loudness	-0.237083	0.698039	0.327036	1.000000	0.189904	0.112837	-0.0
speechiness	-0.021774	0.417214	0.400018	0.189904	1.000000	0.192687	-0.3
tempo	-0.171003	0.201885	0.108855	0.112837	0.192687	1.000000	0.0
valence	-0.138803	0.046217	-0.347451	-0.027571	-0.399751	0.000558	1.0
popularity	0.108046	-0.057272	-0.205845	0.156323	-0.136745	-0.061061	0.0
danceability	0.070017	-0.300536	-0.516387	-0.249406	-0.322684	-0.324398	0.5
instrumentalness	0.061403	0.120261	0.008873	0.012524	0.009586	0.010961	0.1

Observations

1. Popularity:- There is no significant corelation identified between popularity with other features.
2. Energy->loudness,liveness,tempo,accoustic,danceability:- There is positive correlation identified with loudness(.70), liveness(.51) and tempo(.20) whereas negativw correlation identified with danceability(-.30) and accoustic (-.36).
3. Valence-> Danceability:- There is positive correlation (.55) identified with danceability

d. Provide insights on the significance of dimensionality reduction techniques. Share your ideas and elucidate your observations

Dimensions Reduction Techniques

Dimensionality reduction involves decreasing the number of features (or dimensions) in a dataset while preserving as much information as possible. This technique is used for various purposes, such as simplifying a model, enhancing the performance of a learning algorithm, or making the data easier to visualize.

1. Improves computational efficiency: Reduces the computational cost for data processing and model training.
2. Mitigates the curse of dimensionality: Simplifies data to prevent overfitting and sparsity issues.
3. Reduces noise in data: Eliminates irrelevant or noisy features to enhance model performance.
4. Enhances data visualization: Makes high-dimensional data easier to visualize in 2D or 3D.

5. Boosts model performance: Focuses on the most relevant features for better accuracy.
6. Saves storage and memory: Decreases the amount of storage and memory needed for large datasets.
7. Increases model interpretability: Simplifies models, making them easier to understand and explain.
8. Avoids multicollinearity: Addresses high correlation between features to improve regression models.

There are two ways implement this technique.

Feature selection is the process of choosing a subset of relevant features and discarding irrelevant ones from a dataset to build a more accurate model. Essentially, it involves selecting the most optimal features from the input data.

Feature extraction is the process of transforming high-dimensional data into a lower-dimensional space. This approach is useful for retaining essential information while using fewer resources for processing.

Cluster analysis results are visualized using PCA below;-

4. Perform cluster analysis

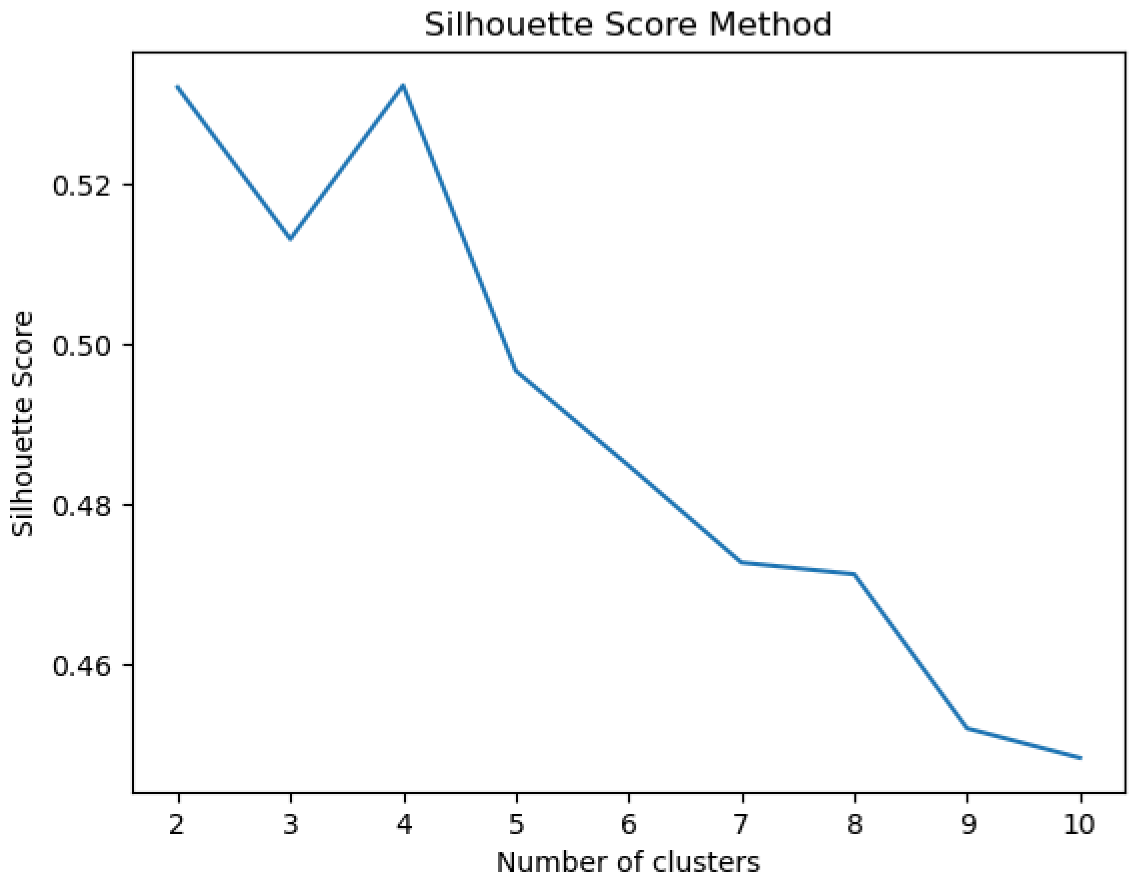
```
a.      Identify the right number of clusters.
b.      Use appropriate clustering algorithms
c.      Define each cluster based on the features
```

In [113…

```
# Identify the right number of clusters
#from sklearn.datasets import make_blobs

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
# Silhouette Score method
columstoscale=['energy','liveness','speechiness','loudness','tempo']
X=df[columstoscale].copy()


silhouette_scores = []
for i in range(2, 11):
    model = KMeans(n_clusters=i, n_init=10,  init='k-means++', random_state=42)
    model.fit(X)
    score = silhouette_score(X, model.labels_)
    silhouette_scores.append(score)

plt.plot(range(2, 11), silhouette_scores)
plt.title('Silhouette Score Method')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')

# Select the number of clusters with the highest silhouette score
optimal_clusters = range(2, 11)[silhouette_scores.index(max(silhouette_scores))]
print("Silhoute Score Method Used:",optimal_clusters)
```

```
print("Optimal Clusters Identified by silhoute score:",optimal_clusters)

plt.show()
X.head(10)
```

```
Silhoute Score Method Used: 4
Optimal Clusters Identified by silhoute score: 4
```



Out[113…

	energy	liveness	speechiness	loudness	tempo
0	0.993	0.932	0.1100	-12.913	118.001
1	0.965	0.961	0.0759	-4.803	131.455
2	0.969	0.956	0.1150	-4.936	130.066
3	0.985	0.895	0.1930	-5.535	132.994
4	0.969	0.966	0.0930	-5.098	130.533
5	0.956	0.741	0.0915	-5.539	101.628
6	0.810	0.972	0.0969	-6.851	77.520
7	0.971	0.993	0.0873	-5.509	128.958
8	0.942	0.959	0.1190	-6.018	139.452
9	0.944	0.974	0.1280	-5.074	119.782

In [113…

```
#KMeans clustering used
# Fit the model with the optimal number of clusters
model = KMeans(n_clusters=optimal_clusters, n_init=15, init='k-means++', random_sta
y_kmeans = model.fit_predict(X)
print('KMeans clustering used')
```

```
KMeans clustering used
```

In [113…

```
#Saving the cluster data
df['cluster']=model.labels_
#df.drop([0:1])
df.to_csv('rolling_stones_spotify_clusters.csv')
print("Data with Cluster Assigned Saved")
df.head()
```

```
Data with Cluster Assigned Saved
```

Out[113…

	Unnamed: 0	name	album	release_date	track_number	id	
0	0	Concert Intro Music - Live	Licked Live In NYC	2022-06-10	1	2IEkywLJ4ykbhi1yRQvmsT	s
1	1	Street Fighting Man - Live	Licked Live In NYC	2022-06-10	2	6GVgVJBKkGJoRfarYRvGTU	s
2	2	Start Me Up - Live	Licked Live In NYC	2022-06-10	3	1Lu761pZ0dBTGpzxaQoZNW	spo
3	3	If You Can't Rock Me - Live	Licked Live In NYC	2022-06-10	4	1agTQzOTUnGNggyckEqiDH	spo
4	4	Don’t Stop - Live	Licked Live In NYC	2022-06-10	5	7piGJR8YndQBQWVXv6KtQw	spo

Clustering Result Analysis

Using Silhouette Score method, number of optimal clusters identified to 4 based on 5 features (energy liveness speechiness loudness tempo)

After observing the clustering results, cluster distribution is more influenced by tempo. Tempo can be encoded into more clearer group (Slow 0, Medium 1, Fast 2).

1. Cluster 0 # High Energy, Moderate Tempo (<127)

2. Cluster 1 # High Energy, Fast Tempo (<160 and >127)
3. Cluster 2 # High Energy, Very fast Tempo (>160)
4. Cluster 3 # High-Low Energy, Low Tempo (<99)

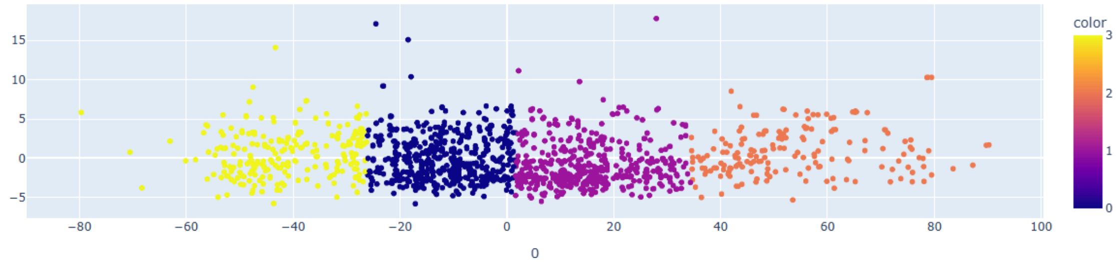
***Tempo is a fundamental aspect of music that dictates how fast or slow a piece should be performed. It serves as the heartbeat of music, influencing the mood, style, and overall expression of a composition. A piece played at a fast tempo can evoke excitement, while a slow tempo may convey calmness or sadness.

Tempo refers to the speed of a song, expressed in BPM (beats per minute).Tempo is tightly linked with perceived energy, mood, and activity suitability of music. Tempo helps differentiate songs into pace categories such as slow ballads, mid-tempo grooves, or fast-paced dance tracks.

For example:

1. Slow tempos: 0-79 BPM
2. Medium tempos: 80-129 BPM
3. Fast tempos: 130+ BPM

Visualizing Cluster Analysis results using PCA



In [113…

```
#Visualizing cluster data using PCA
import plotly.express as px
from sklearn.decomposition import PCA

X = df[columstoscale]
pca = PCA(n_components=5)
components = pca.fit_transform(X)
fig = px.scatter(components, x=0, y=1, color=df['cluster'])
fig.show()
```